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Information Clustering for Better Decision-Making

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PREFACE

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Chunking of information in memory is one of the distinguishing features of expertise. Thus, it is hypothesized that providing information displays that cluster and integrate information according to the expert decision-maker's task leads to more efficient decision performance. Three information format schemes; alphabetical listing, functional partitioning, and integrative clustering were tested for a complex, time-limited task with conflicting goals. The integrative clustering led to the most efficient performance. Functional partitioning required greater effort for limited performance improvement. Results are discussed in terms of implications for display designers.

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INTRODUCTION

This report makes four points relative to the development of interfaces for decision aids to be used by experts. The first three points are background; the fourth is the focus of this study.

1. To solve complex and ill-structured problems, experts use chunks of information, analogous to memory chunks.

2. Decision-making is improved by better organization of the information. (Better organized is defined in terms of the user's task.)

3. Increasingly, complex tasks are supported by computerized aids. The development of these aids is facilitated by a functional partitioning of the tasks for efficient engineering of the algorithms and programs.

4. In contrast to the functional partitioning to meet development needs, decision aids for experts may be improved by information chunking (clustering) that is consistent with the structure of the user's problem-solving schema, i.e., the chunks referred to above. This last point is the kernel of an information-clustering hypothesis that will be developed here.

The context for this report is the development of computerized decision aids for higher-level technical decision-makers. Although originally only used by scientists and engineers, computers are prevalent everywhere today as word processors, data manipulators (via spreadsheets and databases), scheduling aids, and cybernetic sensors and control devices. Computers sit on the desks of most clerical, sales, financial, technical, and managerial personnel, up through middle management.

Computers as decision aids are now reaching into the offices and control rooms of senior decision-makers and managers. For example, the NASA flight control room we have all seen on television is filled with individuals using computers to monitor and control elements of the launch process. However, the test director has only a television screen, a notebook of schedules and protocols, and telephones to aid in keeping the process coordinated and on time (John, Remington, and Streier, 1991). The most important aspect of the test director's job is making decisions when unexpected events and anomalies arise. The need for, and appropriate design of, dedicated computer support is just now being investigated. Because the test director's job is more than the sum of the individual functions, this computer support must not only allow the test director to look over the shoulders of all the individuals controlling specific functions, it must support the integrated evaluation of current status, schedule projections, resources, and limitations in support of efficient scheduling and planning for an on-time and safe launch. Most importantly, computer support must not impose constraints that will inhibit the solution of unique problems. As with support for the test director, the current study focuses on those domains for which the first generation of computer support is being conceived.

EXPERT PROBLEM-SOLVING

The literature on expert problem-solving is too lengthy to be reviewed here. The reader is referred to Chi, Glaser, and Farr (1981) or Ericsson and Smith (1991) for a more complete review of the topic. One point will be discussed here.

Part of the efficiency of expertise can be attributed to the *complied* nature of expert knowledge. Experts systematically use chunks comprised of related items of information during the situation assessment phase of decision-making and problem-solving. These chunks can be identified when experts search for information in a problem-solving, decision-making, or memory task (Kirschenbaum, 1992; Chase and Simon, 1973). The chunking of information in long-term memory is similar (and related) to the chunking effect that improves capacity in short-term memory (Miller, 1956). Evidence that expert knowledge is comprised of chunks of information was first reported by deGroot (1965) in a study of chess masters. In later studies of expert recall of chess positions, Chase and Simon (1973) report that chess masters typically examine and record patterns of positions quickly, with longer latencies between pattern groups. Kirschenbaum (1992) reported a similar temporal indication of the use of chunks of information when experienced submarine officers examined situational data prior to making maneuver decisions. These chunks correspond to aggregated feature components employed by operators working at Rasmussen's (1983) skill-based and rule-based levels of performance. Such aggregated features speed situation recognition and provide access to preprogrammed responses. Another way to think of these chunks is as complied knowledge. Both Anderson's (1983) ACT* and Laird, Rosenbloom, and Newell's (1986) SOAR formalisms make use of this concept to explain how experts perform so effortlessly and quickly, within their area of expertise.

In the past, information displays and analysis tools have comprised the bulk of computerized decision aids. These have been employed by subordinate operators and analysts to perform single-goal (or serial-goal) tasks. Note that hierarchical decision teams are often composed of two (or more) levels of personnel. The lower-level positions are limited in their scope and authority and perform relatively limited and routine tasks directed by higher authority. Technicians, nurses, and sailors are examples. A second hierarchy, usually differentiated by educational credentials, can lead to senior executive level decision authority. Frequently, even the least experienced member of this group is, at least formally, superior to all members of the *lower* group. Examples of these professions are scientists, physicians, and military officers. In each group there is a hierarchy of experience, and movement between groups is rare. The focus of this investigation is the senior expert in the second category who is *doing*, rather than managing, the task.

The task of the senior decision-maker (submarine commanding officer, surgeon, or NASA test director) is to evaluate (integrate, compare conditions to assumptions, assess, etc.) the available information, predict the effects of various action options, and communicate the decision. The available information is composed partially of data previously analyzed by subordinates and partially of unanalyzed raw data. It includes history, current state, predictions, and may contain considerable uncertainty, or may change over time. Required decisions may include both what to do and when to act.

INFORMATION ORGANIZATION

Recent studies (Kleinmuntz and Schkade, 1993) show that *how* a problem is represented affects the speed and accuracy of identifying and assessing the situation, and consequently, the quality of the decisions made with that information. For example, Johnson, Payne, and Bettman (1988) found that display format affects the likelihood of preference reversals (a well-documented decision error) in choice decision-making. Decision-makers in these studies shifted information-gathering strategies as a function of display format. Brown and Klayman (1989) and Smith (1989) found that representation affects subjects' ability to identify key problem elements in naturalistic decision situations. Larkin (1989) has called this effect display-based problem-solving because the availability and form of the information displayed can affect problem-solving. For example, Russo (1977) found that a table of unit prices for an entire category of food-facilitated price comparison and decision-making, as compared to unit prices displayed with each item, although unit prices are calculated by item, not category. One reason for this improvement may be the reduction in working memory load when appropriate information is clustered.

Note that *better organized* is defined in terms of the user's task, not the engineering components or subsystems. Thus, better organization is not necessarily the same as the problem partitioning employed for data analysis or engineering development. In contrast to this user-centered better organization, the term *functional partitioning* will be used to refer to information that is partitioned according to *engineering* function.

FUNCTIONAL PARTITIONING

The world is becoming an increasingly computerized place. Computerized systems are replacing traditional information sources in complex environments like emergency rooms, military operation centers, and power plant control rooms, as well as more mundane offices and institutions. To support these activities, there has been extensive expertise applied to the engineering and mathematics necessary to analyze and reduce massive amounts of real-time data. The engineering approach is to break systems down into their functional components to better facilitate analysis and subsystem development. This has resulted in new ways to reduce, partition, and analyze data. However, the engineering (functional) partitioning of the components has often been carried over to the design of human teams to perform the various tasks. For example, on the modern Navy ship, the team organization parallels the engineering partitioning of the control system. Initially, the human tasks motivated the development of computerized support systems, but today the support systems may dictate the tasks of the humans.

INFORMATION CLUSTERING

Interface design has followed the analytic engineering development because the developers (often wrongly) assumed that the users would partition the task in a like manner. Even when this has been true for single task operators, it has never been true for high-level decision makers. Today, even the operator performing a single task may need to evaluate performance in terms of other tasks, other variables, or the behavior of other operators. Thus, the engineering analysis that is appropriate to equipment may not be consistent with user needs. Even with modern multitasking and multiple windows, functional partitioning according to engineering tasks may hinder efficient cognitive information fusion and integration required in higher-level human problem-solving (or perception). There is a diversity of information that may comprise elements in a single chunk. Herein the term *integrate* will refer to bringing together these diverse elements in a single picture. Integrating information may affect interpretation, in the same way that an interaction affects the interpretation of a statistical result, i.e., it is more than the sum of its parts. Bringing together the elements of a chunk allows the expert to perceive and quickly recognize a known situation in order to respond more efficiently and accurately. Relieving the expert of the need to integrate the elements of a chunk in (human) memory should reduce errors in chunk identification and speed decision-making.

Thus, decision aids for experts performing integrative decision tasks may be improved by employing an organizational schema for the information that is consistent with the deeply structured problem solving schema of the human user. Decision support and information management systems have been seen as both the solution to the real-time, information management problem, and its cause. That is, the additional information that is collected with advanced technology can be presented electronically to the decision makers. Even had it been available, much of the additional information would have been lost in the days of only pencils and paper. However, the complaint today is of information overload.

It is the thesis of this report that (1) the problem is frequently not information overload but lack of structure and organization in information presentation, and that (2) appropriate structuring can lead to more efficient decision-making. These two points are the kernel of a nascent information clustering hypothesis. It builds on the concept of memory chunks by linking them to chunks, or clusters, of information, potentially available in the environment, that can be used in expert decision-making and problem-solving. These clusters may include both overt, perceptual stimuli available to all decision-makers, and structural or configural patterns of stimuli used by knowledgeable experts. The first part of the hypothesis is nothing more than a restating of the well known observations, cited above, viz., that experts use both the surface and deep structural information in decision-making and problem-solving and that they have a large amount of *compiled* knowledge in their area of expertise. The second part of the hypothesis received an initial test in the study reported here.

The experimental task chosen was simulated, on-line, college course scheduling, which has several features in common with other, real-world, complex decision tasks. To simulate an event-driven environment, classes could fill while the *student* was selecting a schedule. When a planned course was filled, the subject had to reassess the situation and find a new course that fulfilled the other requirements. Elements of data history were important because previous semester's records, program requirements, and course prerequisites had to be reconciled. A set of sometimes conflicting goals further constrained choices (see table 1). Lastly, of course, classes could not conflict with one another.

Table 1. Goals, Listed in Priority Order

1. Register for 15 to 17 hours (5 courses).

2. Try to fulfill requirements and prerequisites for both general education and your major. (Note that you may remain an industrial engineering major or select engineering psychology.)

3. Try to schedule courses to allow one full day or two half days off. (One full day is preferable. Assume that you have a job and will otherwise have to work on the weekend.)

4. Try to get the best instructors possible. (On page 35 there is a list of instructor ratings from a student survey.)

5. Try to avoid 8 a.m. classes.

The scoring scheme operationalized each of these elements as values associated with accomplishing the goals and values for each of the choices (i.e., courses and instructors). It was predicted that scores would reflect the level of organization in the display schema, with better performance, less effort, and shorter time-on-task for the better organized displays.

METHOD

SUBJECTS

The two *a priori* requirements for subjects were that they be recent college students with a minimum of eight semesters and that they had registered for college classes within the past 5 years. Thus, they could be considered experts at the putative task. There were 10 women and 26 men evenly distributed across the three conditions (designated A, B, and C). They had last registered for college courses an average of 2.86 years ago. The educational level of the sample ranged from bachelor to doctorate degrees. All subjects ranged from experienced to expert computer users, according to self-ratings. The subjects did not differ significantly on any relevant measures. All were volunteers and were not paid to participate in this experiment.

APPARATUS AND MATERIALS

Three prototype information presentation formats were developed using Supercard on a Macintosh IIfx computer with a 19-inch color display. Conditions A and B used a booklet-like format with only a single page visible at a time. The page numbers in the Table of Contents functioned as buttons to provide access to any category of information. Categories are listed in table 2, which is actually the table of contents for condition B.

In condition A, all information in the course schedule and prerequisites sections was listed in alphabetical order. Because courses were not listed by course title (only course number) in the requirements and student record sections, this format required a search information retrieval strategy.

In condition B, course schedule and prerequisites were listed by department and sequentially by number within a department. This partitioning into departmental groupings was analogous to the functional organization employed by many current engineered systems.

Condition C used a format that supported information clustering for better integration of requirements, course availability, student record, and prerequisites information. It used a computer registration analogy with access to information via a menu. Multiple movable windows were available simultaneously. These were scrollable and resizable when required (e.g., course schedule, registration card, and any other card with more than about 10 lines of information). Information clusters were determined by analyzing the steps required to select a single course. Pilot testing confirmed the cluster contents. An example of a single cluster included requirements, course prerequisites, courses already taken, and times of potential courses. Prerequisites and courses already taken were provided within the windows listing course schedules. Requirements could be observed simultaneously with other windows.

Table 2. Categories of Information in Table Of Contents: Functional Display Format

Table of Contents

DESIGN

The task was a second-year college registration. Subjects were given goals, student records of course and grade history, prerequisites, a campus map with walking times, and instructor ratings. The task was timed and courses closed dependent on the elapsed time. The experiment used a between subjects design with 12 subjects per group. Three classes of dependent measures were used. The first was total time-on-task (T), the second reflected outcome performance (P), and the third measured processing activity (A).

Performance was defined as the summation of the following four performance measures: the number of credits successfully registered (P1), the sum of the requirements scores for all courses registered (P2), the sum of the scheduling difficulty scores for all courses registered (P3), and the average preference score for the instructors of all selected courses (P4). Each of the four scores was determined *a priori* and was reflected in the goal set given to the subjects.

The processing measures captured various aspects of the effort that subjects put into the task. These included, number of registration attempts (A1), number of class close-outs (A2), number of windows used (A3), and number of times the subject iterated back and forth between any two windows (A4). One full cycle from window a to b to a to b was counted as one iteration. These measures were combined into an overall efficiency measure. Efficiency, E, was defined as a function of mean overall performance, m(Pi), mean amount of processing, m(Aj), and total time-on-task required to achieve that level of performance, T:

$$E = m(Pi)/m(Aj) + T.$$

PROCEDURE

The experiment took place in a small, sound-damped, experimental room. All instructions were presented on the computer screen. Subjects were given introductory instruction on the manipulation of objects used in the program and on the task. There was a practice task for each condition that duplicated all of the screens, interactions, and information types. During the practice and before the actual experimental trial, subjects were invited to ask questions, however, questions about strategy were not answered. No questions were answered after the experimental trial began. At the end of the experimental task, subjects were asked to complete a computerized questionnaire and were debriefed. The questionnaire was designed to ascertain recall of relevant information, task strategy, computer and college registration expertise, and any comments about the experiment.

RESULTS

The groups did not differ on any of the measures of computer experience or college registration experience. Table 3 shows means and standard deviations for all behavioral measures (T, P, A, and E). To facilitate comparisons among measures, all scores were transformed into standard scores with a mean of 50 and a standard deviation of 10.

Table 3. Means and Standard Deviations for All Measures for All Groups

	Alphabetical		Functional		Integrated	
	M	SD	M	SD	M	SD
Performance Measures						
P1	48.40	11.77	50.97	6.36	50.60	11.62
P2	48.33	12.20	50.17	8.87	51.52	9.23
P3	49.65	10.07	47.69	11.35	52.59	8.73
P4	49.67	11.46	46.61	8.60	53.82	9.29
Process Measures						
A1	48.89	5.43	53.47	15.04	47.21	5.76
A2	51.01	12.33	52.15	10.93	46.44	3.95
A3	55.78	8.98	54.21	7.60	40.02	3.92
A4	56.65	9.65	53.84	6.37	39.51	0.42
Time-on-task	49.24	9.76	52.54	10.62	48.21	9.94
Efficiency	0.48	0.07	0.47	0.09	0.58	0.08

EFFICIENCY

Major interest was in the efficiency of decision-making with the three formats. Subjects who used the integrated information format were significantly more efficient in their decision-making than were those using either of the other two formats, $F(2,33) = 7.29$, $p < .005$ (see figure 1). This was a robust effect, with $h^2 = 0.32$. In a *post hoc* test for trend, the quadratic trend was significant, $F(1,33) = 4.32$, $p < 0.05$.

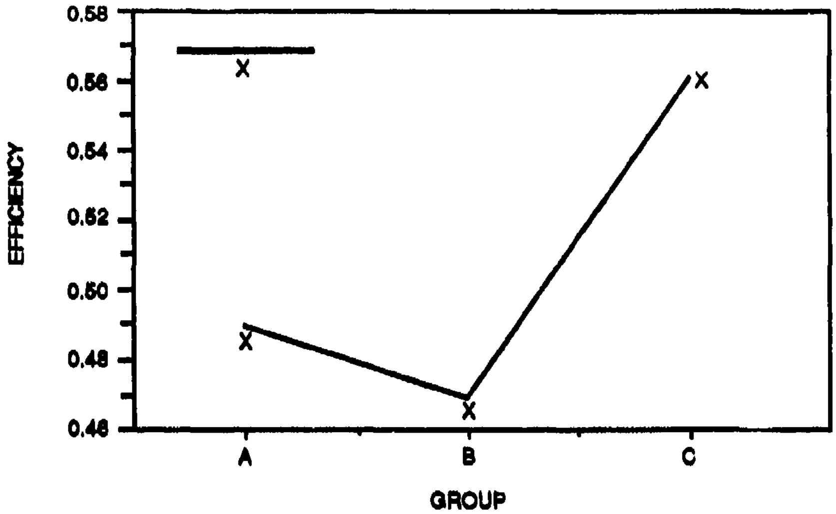

Figure 1. Efficiency for Each of the Three Display Formats (performance divided by processing effort and time)

PROCESSING MEASURES

Detailed examination of the data shows the contribution of performance, processing, and time to overall efficiency. The process measures showed two patterns of behavior (see figure 2). For ease of analysis and discussion, these shall be called $A_{1,2}$ and $A_{3,4}$, with the understanding that the two components of each compound measure displayed the same pattern of results. The first compound measure was composed of measures A_1, registration attempts, and A_2, number of close-outs. These are both indications of difficulties with the task, rather than the display format. There were no significant differences among the conditions on this compound measure, $F(2,33) = 1.71$, n.s.

The second pair of processing measures; A_3, number of windows and A_4, number of iterations, are indications of information usage and ease of access for each display format. There were significant differences among the groups on this pair of measures, $F(2,33) = 43.04$, $p<0.001$. This was a very robust effect with $h^2 = 0.72$ and, in a *post hoc* test for trend, the quadratic trend was significant, $F(1,33) = 13.104$, $p<0.005$.

The iteration measure was particularly interesting. In conditions A and B, subjects iterated between members of information clusters, while in condition C, they typically positioned information windows so that all members of relevant clusters were visible simultaneously. Thus, a high number of iterations is indicative of an unsupported memory load requiring subjects to return to the previous window to re-access information. A typical pattern for the subjects in condition A was to iterate between the schedule page and virtually every other page. However, there were numerous iterations among other pages. For subjects in condition C, virtually all of the iterations were between the schedule page and one of the pages listing course schedules. There were very few iterations for subjects in condition C, and these were different for each subject. Figure 3 shows typical patterns of iterations for subjects in each of the three conditions.

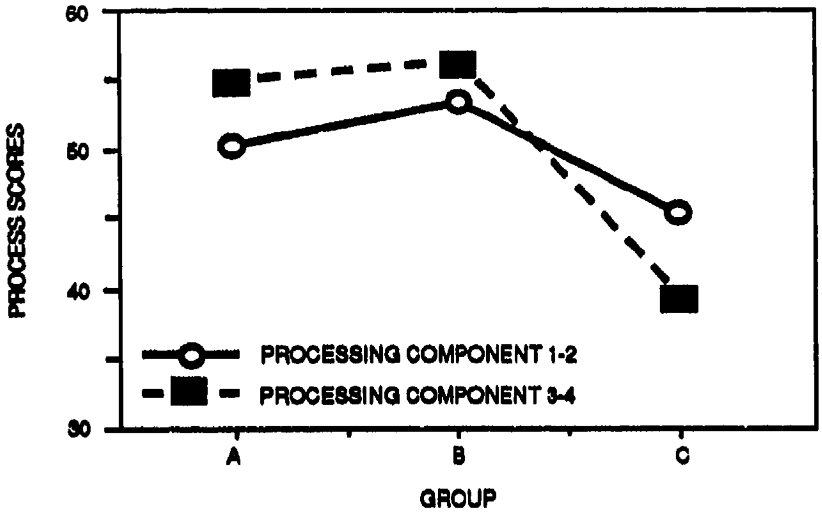

Figure 2. Mean Processing Score on Two Compound Measures for Each Display Format

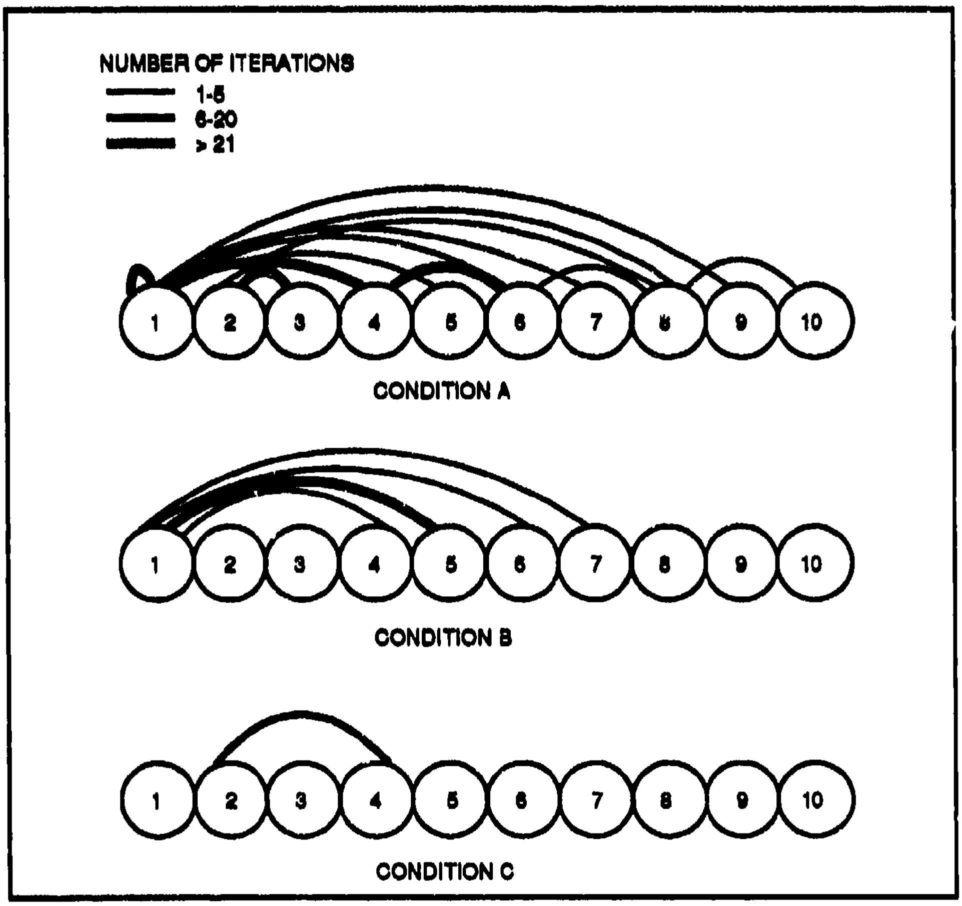

Figure 3. Typical Patterns of Iterations for Subjects in Each of the Three Conditions

TIME-ON-TASK

While means were not significantly different among groups, variances were large, and time-on-task did contribute to individual performance differences. Thus, to account for differences in time taken by individual subjects, performance was computed per unit time.

PERFORMANCE MEASURES

The performance measures appeared to be composed of two compound measures that behaved very differently (see figure 4). The first, $P_{1,2}$, was composed of the more concrete performance measures; P_1, the number of credits successfully registered and P_2, the sum of the requirements scores for all courses registered. The tasks represented by these measures were essential for completion of the course schedule and did not reflect differences in performance. They replicated minimal or baseline performance. Although there appears to be a slight trend toward better performance for groups B and C, this was not significant, $F<1.0$.

The second compound performance measure, $P_{3,4}$, was composed of more difficult, evaluative, and integrative tasks; P_3, the sum of the scheduling difficulty scores for all courses registered, and P_4, the average preference score for the instructors of all selected courses (see figure 4). These measures appeared to reflect an added effort to perform well, when possible. $P_{3,4}$ showed a paradoxical dip in performance with the functional display organization, B. This quadratic trend was marginally significant, $F(1,33) = 4.07$, $p = 0.05$.

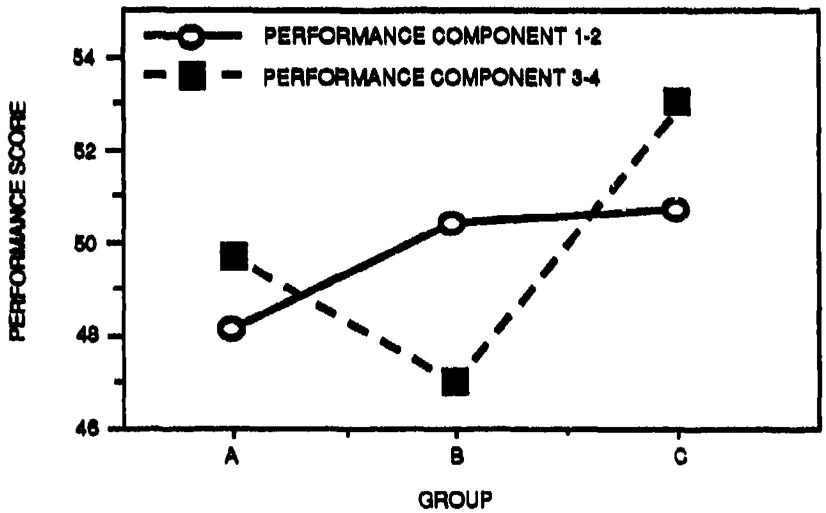

Figure 4. Mean Performance on Two Compound Measures for Each Display Format

To complete the picture, the relationship between performance and process measures was analyzed. This relationship can best be understood by examining figure 5. As can be seen, there was an inverse relationship among these measures. Processing variables were moderately predictive of total performance score, $R^2 = 0.42$.

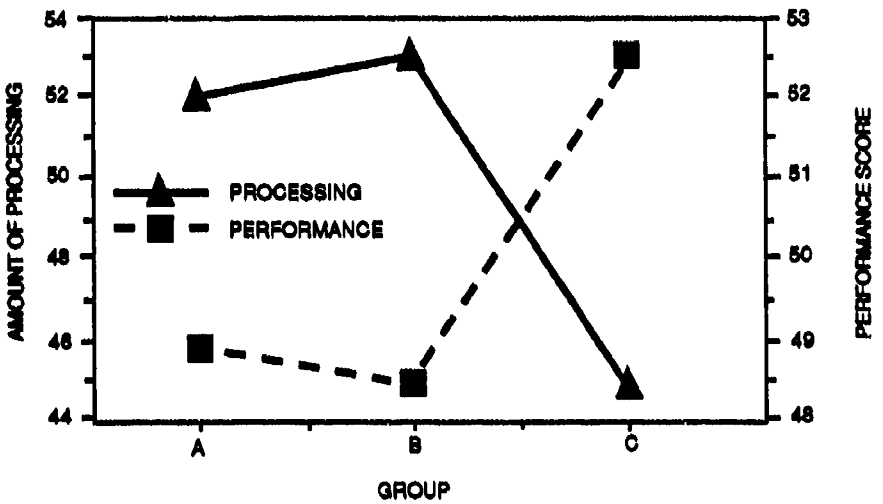

Figure 5. The Relationship Between Performance and Process Measures for Each Format

CONCLUSIONS AND RECOMMENDATIONS

Overall, the results indicate the importance of information clusters and accessibility for efficient executive decision-making. More detailed examination of these data imply a relationship between memory load and processing load (effort) for information usage requirements. The iteration measure is especially interesting because it is an indication of whether the clusters provided met the needs of the decision-maker. It is assumed that, where the user iterated between any two windows several times, she or he was creating, in memory, the clusters that the display did not provide.

These results support the information clustering hypothesis. The three versions of this task had the same performance requirements and provided the same information to the subject, but group C, using the display that clustered information according to task requirements, was significantly more efficient than either of the other groups. Interestingly, there was no significant difference among the groups on the gross performance measure, or on the easy performance component, $P_{1,2}$, but there was a significant difference on the more difficult component, $P_{3,4}$. More importantly, the trend of this relationship was quadratic, indicating that performance *decreased* for the group using the functional partitioning information schema. This same shape trend was found for processing component $A_{3,4}$ and for the gross efficiency measure.

These three trends, taken together, suggest that a functional partitioning of data can actually be detrimental when the user is doing an integrative task. As usual, the key to designing appropriate display schemas is to understand the user's task. For the senior, executive-level decision-maker, the task is frequently integrative. Providing only the decomposed functionality is like examining the results of a factorial study without considering interaction effects.

These results suggest that a display that organizes information according to function can actually hinder efficient performance when the task requires integration of information. They show that a functional display organization leads to longer time to decide, poorer performance on some aspects of decision-making, and lower efficiency, as compared to integrated organization. This result is only reasonable if the task requires integration of information from many *functions*. The functional display organization is reasonable if the task requires *performing* the function, but not if it requires using the results of the function to make decisions.

While decision aids have always been developed by analyzing perceived needs, a radically different suggestion is to design information management decision aids the way new walkways are sometimes planned. That is, where natural paths occur because of repeated use by pedestrians, constructed (concrete, macadam, gravel, etc.) pathways are built. These are not planned *a priori*, but develop from use. Only after the grass has been worn, are constructed paths built. In the same way, the interface designer might track the way users employ their minimally constrained systems and then build easy access paths among frequently used items, or even allow the user to build them. The naturally occurring pathways worn into the grass are indications of natural chunks that can better support executive decision-making.

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Carnegie-Mellon University (B. John)	1
Klein Associates, Fairborn, OH (G. Klein)	1
Virginia Polytechnic Institute and State University (K. Williams)	1